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Measuring Team Knowledge

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ABSTRACT

Multioperator tasks often require complex cognitive processing at the team level. Many team cognitive processes such as situation assessment and coordination are thought to rely on team knowledge. Team knowledge is multifaceted and comprised of relatively generic knowledge in the form of team mental models and more specific team situation models. In this methodological review paper, recent efforts to measure team knowledge are reviewed in the context of mapping specific methods onto features of targeted team knowledge. Team knowledge features include type, homogeneity vs. heterogeneity, and rate of knowledge change. Measurement features include knowledge elicitation method, team metric, and aggregation method. When available, analytical conclusions or empirical data that support a connection between team knowledge and measurement method are highlighted. Also, empirical results concerning the relation between team knowledge and performance are presented for each measurement method described and research and methodological needs are identified.

Measuring Team Knowledge

Technological developments in the workplace and elsewhere have drastically changed the nature of many tasks (Howell & Cooke, 1989). What were once highly repetitive tasks, requiring practiced motor skills, are now tasks that require cognitive skills often related to overseeing new technology such as monitoring, planning, decision making, and design. As a result, a full understanding of many tasks requires an examination of their cognitive underpinnings. Taking a cognitive engineering perspective, these cognitive factors need to be examined in the context of the larger sociotechnical system in which they are embedded (Hutchins, 1995; Norman, 1986, Woods & Roth, 1988).

For instance, the growing complexity of tasks frequently surpasses the cognitive capabilities of individuals and thus, necessitates a team approach. Teams play an increasingly critical role in complex military operations in which technological and information demands necessitate a multioperator environment (Salas, Cannon-Bowers, Church-Payne, & Smith-Jentsch, 1998). In addition, civilian applications ranging from manufacturing to nuclear power plant operation and computer-supported collaborative work also require a team perspective (e.g., Sundstrom, DeMeuse, & Futrell, 1990).

Salas, Dickinson, Converse, and Tannenbaum (1992) define *team* as "a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, who have each been assigned specific roles or functions to perform, and who have a limited life span of membership" (p. 126-127). Thus, teams, unlike some groups, have differentiated responsibilities and roles (Cannon-Bowers, Salas, & Converse, 1993). This division of labor enables teams to tackle tasks too complex for any individual.

Whereas the team approach is often seen as a solution to cognitively complex tasks, it also introduces an additional layer of cognitive requirements that are associated with

the demands of working together effectively with others. Team members need to coordinate their activities with others who are working toward the same goal. Team tasks often call for the team to detect and recognize pertinent cues, make decisions, solve problems, remember relevant information, plan, acquire knowledge, and design solutions or products as an integrated unit. Therefore, an understanding of team cognition, or what some have called the new "social cognition" (Klimoski & Mohammed, 1994), is critical to understanding much team performance.

Parallel to research on individual expertise (e.g., Chase & Simon, 1973; Glaser & Chi, 1988), accounts of effective team performance highlight the importance of knowledge, or in this case team knowledge. For instance, Cannon-Bowers and Salas (1997) have recently proposed a framework which integrates many aspects of team cognition in the form of teamwork competencies. They categorize competencies required for effective teamwork in terms of knowledge, skills, and attitudes that are either specific or generic to the task and specific or generic to the team. Similarly, a team's understanding of a complex and dynamic situation at any one point in time (i.e., team situation awareness) is supposedly influenced by the knowledge that the team possesses (Cooke, Stout, & Salas, 1997; Stout, Cannon-Bowers, & Salas, 1996). In this paper we examine the measurement of team knowledge, describing methods and metrics that have been used, proposing additional measures, and identifying research and methodological needs where appropriate. First, however, we define team knowledge.

Team Knowledge: A Definition

The knowledge possessed by effective teams has been frequently referred to as shared knowledge and in similar contexts, as shared mental models, shared cognition, and shared understanding (Blickensderfer, Cannon-Bowers, & Salas, 1997b; Cannon-Bowers, et al., 1993; Converse, Cannon-Bowers, & Salas, 1991; Klimoski & Mohammed, 1994; Kraiger, Krause, & Hart, 1996; Kraiger & Wenzel, 1997; Orasanu, 1990; Rentsch & Hall, 1994; Robertson & Endsley, 1997; Rouse, Cannon-Bowers, &

Salas, 1992; Sarter & Woods, 1991; Stout, et al., 1996). Such knowledge sharing is thought to help teams coordinate implicitly when explicit communications are hampered, thereby enhancing team performance (Cannon-Bowers, et al., 1993; Kleinman & Serfaty, 1989; Stout, et al., 1996). For example, Cannon-Bowers, et al., (1993) suggest that shared mental models provide mutual expectations which allow teams to coordinate and make predictions about the behavior and needs of their teammates.

To date, there has been much conceptual work on shared mental models. Notably, Cannon-Bowers, et al. (1993), Kraiger and Wenzel (1997), and Klimoski and Mohammed (1994) have provided extensive reviews of work in this area, and all have attempted to explicate the relationship between shared mental models and team performance. Others have tied shared mental models to other constructs such as team situation awareness (Orasanu, 1990; Robertson & Endsley, 1997; Stout, et. al., 1996; Wellens, 1993) and team decision making (Walsh, Henderson, & Deighton, 1988). In addition, there are many factors such as team size, task type, team experience, training, and team process behaviors that are hypothesized to affect and be affected by shared mental models (Cannon-Bowers, et al., 1993; Klimoski & Mohammed, 1994; Kraiger & Wenzel, 1997). Throughout this literature, researchers have pointed to the measurement of shared mental models as the missing link between conceptualization of shared mental models and further research on the construct. Therefore, we take this conceptual work on shared mental models as a point of departure and begin to identify and address issues in the measurement of team knowledge.

As a first step in this process, a specific definition of the term *team knowledge* is required. We prefer the term *team knowledge* over *shared mental models or shared cognition* for several reasons. First, the use of the term *team*, as described previously, restricts the problem domain to knowledge possessed by teams, as opposed to dyads or groups in general, the targets for related work such as common ground in discourse (Clark, 1994) and group information processing (Hinsz & Tindale, 1997). Second, we

prefer to avoid use of the term *shared* because, as we discuss later, *share* can mean to hold in common or to apportion and the ambiguity can create confusion, especially in this context. Finally, we use the term *knowledge* rather than the broader term, *cognition* because the latter would include a wide range of cognitive phenomena at the team level such as team decision making, team vigilance, and team situation awareness. Whereas much of team cognition relies heavily on team knowledge, the former is beyond the scope of this review. Thus, this paper focuses on team knowledge which is a subset of team cognition as represented in the framework of Table 1. Furthermore, we prefer the term *knowledge* over the narrower term, *mental model* in order to capture the two facets of team knowledge also illustrated in Table 1.

[Insert Table 1 about here]

In their synthesis of the literature, Cannon-Bowers, Salas, and Blickensderfer (1999) distinguish two types of team knowledge. Team mental models refer to the collective task- and team-relevant knowledge that team members bring to a situation. Such knowledge is acquired by team members through formal training, experience, team discussions, and the like and is relatively long lasting.

The knowledge associated with the team mental model may be declarative (i.e., the facts, figures, rules, relations and concepts in a task domain), procedural (i.e., the steps, procedures, sequences, and actions required for task performance), or strategic (the overriding task strategies and knowledge of when they apply) (see Stout, et al., (1996) for further explanation). Its content can include knowledge relevant to teamwork such as knowledge of team member roles and responsibilities and knowledge of teammates' knowledge, skills, abilities, beleifs, preferences, and style, as well as knowledge relevant to taskwork such as cue-strategy associations, understanding of task procedures, and knowledge of typical task strategies (see Cannon-Bowers , Tannenbaum, Salas, and Volpe (1995) for more on required knowledge in teams). The team mental model provides a collective knowledge base for team members to draw upon when task episodes

ensue. We assume that the content of the team mental model is critically related to effective team performance.

In addition to team mental models, another type of team knowledge, the team situation model, develops in situ while the team is actually engaged in the task (Orasanu, 1990). At the individual level team members acquire a specific understanding of the current situation at any one point in time (i.e., a situation model). This understanding should change with changes in the situation and thus, Cannon-Bowers, et al., (1999) refer to it as dynamic understanding. The team situation model is the team's collective understanding of the specific situation.

According to Cannon-Bowers, et al. (1999), this type of team knowledge is qualitatively different from that associated with the team mental model, in that it makes use of the pre-existing team mental model, but goes further by incorporating the specific characteristics of the current situation. For example, during task performance, team members interpret cues and patterns in a situation (Stout, Salas, & Cannon-Bowers, in press). The collective outcome of these interpretations is influenced by team mental models and by processes employed by team members (e.g., the clarity of team communications) (Stout et al., 1996).

The team situation model guides the team in assessing additional cues and patterns in the situation, determining strategies available to the team, assessing how the team is proceeding, predicting what teammates will do and need, and selecting appropriate actions to take. Thus, the degree to which teammates are coordinated in these judgments is crucial to team performance and depends on the team situation model.

In sum, the term knowledge is meant to extend beyond mental models of a system, to include knowledge about other task and team-relevant areas, as well as the more fleeting interpretation of the current situation. The use of the term knowledge is also meant to be neutral as to the accuracy or completeness of that information, a dimension which can however, be assessed with access to a definitive standard as discussed later.

In addition, we use the term knowledge pragmatically, assuming little about its form of representation (i.e., connectionist networks, images, symbolic networks) or even the importance of representation. Instead we assume that teams, like individuals, possess knowledge and that this knowledge is reflected in actions or behaviors that provide us with approximations of that knowledge that can be applied to training and design.

Thus, team knowledge can be defined as the collection of task- and team-related knowledge held by teammates and their collective understanding of the current situation. Team performance will be maximized to the extent that team knowledge is accurate, appropriately apportioned among members, and structured in such a way as to support compatible assessments of the task situation and development of effective team strategies to cope with it (Cannon-Bowers, et al., 1999).

Measuring Team Knowledge: A Methodological Review

Although team knowledge and related constructs have been assumed to be critical aspects of team performance, there has been minimal empirical work to support this claim. Research has been focused on the conceptualization of the construct and empirical investigations await the development and evaluation of measures of team knowledge. Measures of team knowledge are not only needed to better understand the underpinnings of effective team performance, but in addition, they are central to knowledge-intensive applications such as team training programs or the design of knowledge-aiding technologies (e.g., Neerincx & deGreef, 1998, Stout, et al., 1996). The content and structure of team knowledge associated with effective team performance can feed directly into the content of training materials. In addition, such information can be used to assess the current state of a team's knowledge in order to identify training needs or evaluate the success of training interventions. In the remainder of this paper we review methodological research directed at the measurement of team knowledge in the context of the goal of mapping the characteristics of the targeted team knowledge onto the specific measurement approach.

Measures can only be evaluated in the context of the measurement target. For instance, the average height of a team's members is not alone a valid or invalid measure unless a target such as team basketball skill or team intelligence is revealed. Similarly, measures of team knowledge should be developed, applied, and evaluated in the context of the targeted team knowledge. This is because team knowledge is multifaceted and different measures will yield different information about team knowledge. In the context of knowledge elicitation methods for individuals, the proposal that different methods elicit different types of knowledge, has been labeled the differential access hypothesis (Hoffman, Shadbolt, Burton, & Klein, 1995). In fact, the methods can be viewed as tools in a tool kit (or paints on a palette (Hoffman, et al., 1995)) and one would not select a hammer to tighten a screw. Congruent with this analogy, it is likely that multiple "tools" are required to measure a specific aspect of team knowledge (Hinsz, 1995; Kraiger & Wenzel, 1997).

Thus, our review of team knowledge measures focuses on both the targeted characteristics of team knowledge, as well as the characteristics of the measurement approach. Figure 1 provides an advanced look at the characteristics of each which are covered in detail in our review. Note that these characteristics are not meant to completely capture team knowledge or team knowledge measures; yet they are representative of our current thinking, as well as that of the recent literature. Ideally, as also represented in Figure 1, the characteristics of the targeted knowledge should map directly onto a specific measurement approach. Mappings suggested by the sparse literature in this area are highlighted in this review. Other unaddressed mappings can best be viewed as a guide for additional research in this relatively new area. The review begins with identification of the features of team knowledge that should be considered in selecting a measurement approach.

[Insert Figure 1 about here]

Characteristics of Team Knowledge

In general, the type of team knowledge that is targeted depends on the subject domain and the purpose of the measurement. For instance, in order to assess a team's situation awareness for training purposes in a highly dynamic cockpit environment, one may target situation models However, if measurement were done in the context of a design group with the purpose of facilitating the team design process, then mental models of the task may be targeted.

In Figure 1, three dimensions along which team knowledge varies are represented: 1) mental models vs. situation models, 2) homogeneous vs. heterogeneous knowledge distribution, and 3) rate of change. The distinction between team mental models and team situation models was discussed in the previous section. Further, this distinction can be extended by including more specific characterizations of knowledge such as the form (i.e., declarative, procedural, strategic) and the content (i.e., taskwork, teamwork) of the team knowledge. The second and third distinctions are described in the sections that follow.

Heterogeneity and Knowledge Distribution

It has been suggested that the view that effective teams have shared knowledge or shared mental models in the sense of common or similar knowledge is overly simplistic. Instead, team members may hold in addition to common knowledge, compatible or complimentary knowledge (Cannon-Bowers & Salas, 1997; Klimoski & Mohammed, 1994). That is, there may be some knowledge overlap required among team members, but in addition role-specific, yet compatible knowledge is required. Such team heterogeneity, in which different team members are assigned different roles, is featured in the well-accepted definition of teams offered earlier and seems characteristic of some of the most interesting team tasks. Consider, for example, a surgical team. In some instances, the nurse and the surgeon may need to have some knowledge that is held in common. However, the nurse is not likely to be able to understand, or need to

understand, all of the surgeon's knowledge; hence, he or she must have some knowledge that is compatible with the surgeon's knowledge, but not necessarily identical.

Cases in which team knowledge is identical or completely distinct are highly unlikely (Rentsch & Hall, 1994). In fact, common team knowledge in its extreme would seem ripe for groupthink (Janis, 1972) and according to Klimoski and Mohammed (1994) "...completely overlapping team mental models are viewed as dysfunctional with regard to team performance" (p. 420). That is, tasks that require teams are likely to be tasks which are so complex that they need to be divided among several individuals who are responsible for distinct subtasks. Cannon-Bowers, et al. (1993) also take the view that whereas a certain degree of overlap among mental models of team members is needed for effective coordination and shared expectations, there is also probably a point at which too much overlap will result in group think or become a liability. For instance, in the domain of group decision making, Walsh et al., (1988) assume that knowledge similarity is undesirable.

One source of confusion in regard to this issue and alluded to earlier is that the term *shared* has multiple senses (Klimoski & Mohammed, 1994). Share can mean to have in common (as in share the equipment or share the belief) or it can mean to divide (e.g., share the workload or share the dessert). Likewise, *shared knowledge* may refer to either knowledge that is similar within a team (i.e., homogeneous with respect to team members) or knowledge that is distributed among team members (i.e., heterogeneous). For most tasks, both situations are likely to exist . Therefore, whereas the dichotomy represented in Figure 1 may be appropriate for describing specific units of team knowledge, a point on a continuum ranging from homogeneous to heterogeneous is probably more descriptive of team knowledge as a whole.

Assuming some degree of knowledge heterogeneity on the team, it is necessary to understand the distributional requirements of the knowledge base that are associated with effective team performance. Each team member fulfills an independent role on the team,

as well as an interdependent role as team member. Therefore, measuring team knowledge is not simply a question of measuring everything each team member knows. Instead, it is necessary to discriminate between knowledge that is unique to each team member and required by other team members, as opposed to unique knowledge which is only required by the individual in that role. Thus, the measurement target is not all that a team knows, but within the confines of a specific task and environment, the knowledge required by interdependent team members and its distributional characteristics across those team members.

Rate of Change

Rate of change indicated in Figure 1 has to do with the speed with which the team knowledge changes, with slow, average, and fast being arbitrary markers on a continuous scale. Change is a integral feature of team knowledge. Team knowledge often exists within the context of a dynamic environment. Thus, the team situation model is in a constant state of flux.

In addition, the longer-lasting team mental models, like individual mental models, evolve with experience and knowledge acquisition. However, in the team domain, changes can be expected to occur much more rapidly than at the individual level, because any individual change can potentially change the overall team knowledge. Change is likely to be even more exaggerated in experiments in which college undergraduates with little or no task experience serve as team members. In short, measuring team knowledge under these dynamic conditions is tantamount to aiming at a moving target.

As an initial solution, investigators have opted for knowledge measures taken at several discrete points during an experimental session (e.g., Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, in press), however, repetitive interruptions of a team for elicitation during a task can also be disruptive and the result is more like a series of static snapshots, rather than a continuous video record. Given, the predominance of task domains at the fast end of the rate of change scale, more attention needs to be directed at

data collected continuously and synchronously with task performance (i.e., video records, computer event records, communication records, performance measures).

The characterization of targeted team knowledge in terms of type, distribution, and rate of change, paves the way for the selection of a measurement approach. In the following sections features that differentiate various approaches are described.

Characteristics of Measurement Approaches

Measurement approaches can be characterized by the three features that are represented in Figure 1 (1) elicitation method, 2) team metric, and 3) aggregation method) and described in detail in the sections that follow. These features together comprise what might be called a *collective* approach to measuring team knowledge. That is, team knowledge is viewed as a collection of the knowledge of the individual team members. This approach is representative of the research to date on the measurement of team knowledge. However, before describing the features of the collective approach we introduce an alternative approach which might be labeled a *holistic* approach to team knowledge measurement.

Klimoski and Mohammed (1994) point out that team knowledge is more than the collection of knowledge of individual team members, but instead emerges as a result of interactions among team members. In fact, Hutchins (1991) demonstrates through simulation that team knowledge can be more than knowledge external or internal to team members, but is the consequence of interactions of factors in the sociotechnical system. This concept of emergent knowledge in the context of the collective and holistic approaches is illustrated in Figure 2. Whereas the collective approach targets the knowledge of individual team members and then aggregates this information, the holistic approach targets the team knowledge that results from the application of team process behaviors (i.e., communication, situation assessment, coordination) to the collective knowledge. Thus, the holistic target mediates between team process behaviors and team performance. It can be conceptualized as effective team knowledge or the knowledge

that is revealed in the team's actions. Whereas both collective and holistic targets should ultimately be reflected in team performance, the holistic target is more directly relevant. In short, the result of the collective approach underestimates the importance of team process behaviors in determining what the team knows, and simply assumes that team knowledge is equivalent to the sum of what each team member knows.

[Insert Figure 2 about here.]

For example, in the case of a two-person cockpit crew, the pilot may know of impending threat at point A and the co-pilot knows of a threat at point B. The aggregation of these two facts represent the outcome of the collective approach. However, the outcome of the holistic approach might differ. In the case of poor team process (e.g., perhaps silence on the co-pilot's part due to authority issues), effective team knowledge may be less than this (knowledge of threat at point A only). This could be reflected in the team's decision to progress to point B. Alternatively, more effective team process may lead the team to put their information together, along with their background knowledge, to infer that there is also a probable threat at point C. Again, such knowledge would be reflected in their behavior and ultimate selection of a destination.

A holistic approach to knowledge measurement would require new methods, perhaps interviewing the team as a whole, for instance. The holistic approach also raises a host of interesting questions such as the impact of social or political roles on the outcome of the elicitation. Research is clearly needed to comparatively evaluate collective and new holistic approaches. This said, the measurement characteristics discussed in this section pertain to the collective approach in that elicitation of team knowledge is conducted at the individual level and aggregated across team members to reflect team knowledge.

Knowledge Elicitation Method

Team knowledge measurement, like individual knowledge measurement, requires methods that go beyond assessment of knowledge accuracy to capture the richness of the

knowledge itself. Two individuals may perform at similar levels of accuracy, but have widely different views of the situation. Thus, meaningful judgments about team knowledge are impossible to make on the basis of accuracy alone. The measure must include information on the content and structure of the team's knowledge. Knowledge elicitation methods have been used to satisfy these goals at the individual level and recently investigators have begun to apply these methods to the team level (e.g., Gualtieri, Fowlkes, & Ricci, 1996; Kraiger, et al., 1996; Mathieu, et al., in press; Stout, 1995; Minionis, Zaccaro, & Perez, 1995; Walsh, et al., 1988).

At the individual level, knowledge elicitation is the practice of explicating the domain-related knowledge, often mental model-like knowledge, held by an individual. In many cases the individual is an expert in the domain and the elicitation is conducted with the goal of better understanding the domain. More detailed definitions, along with historical development of the enterprise and associated issues can be found in Cooke (1994), Cooke (1999), and Hoffman, et al. (1995).

A wide variety of knowledge elicitation methods has been applied to the elicitation of knowledge at the individual level. Most of these methods fall into one of the four categories listed in Figure 1 : 1) observations, 2) interviews and surveys, 3) process tracing, and 4) conceptual methods. Each category contains a number of methods that vary in terms of the specific procedure and the type of knowledge that is targeted. Whereas details can be found in the aforementioned reviews, a brief overview of each category and its relevance to team knowledge measurement follows.

<u>Methods for eliciting knowledge.</u> Observations can take written, audio, or video forms and have the potential to provide vast amounts of information in the context of performance, while interfering minimally with tasks. Thus, observations of team behavior provide a continuous source of data that reflects team knowledge. These data could potentially serve as an alternative to static snapshots of team knowledge in cases in which rapid change is indicated. Variations within the category of observational methods

revolve around issues of how to observe (passively or actively) and what to observe (predetermined features or specific aspects of the task and environment). The advantage of minimal intrusion is offset by difficulties interpreting the data. Recently, however, tools to aid in this process such as video analysis software have been developed (Harrison & Baecker, 1991).

Interviews and surveys, like observations, are excellent for gaining a general understanding of the situation, and generating and verifying hypotheses. Unstructured interviews are free-form in that neither content nor sequencing is prespecified. Structured interviews follow a predetermined format and can vary from highly rigid to only loosely constrained. Although structured interviews require more preparation time than unstructured interviews, they also have advantages of being more systematic, and therefore more complete and comfortable for both participants. With enough structure, a structured interview can be converted into a paper-and-pencil measure, such as a survey or questionnaire which are often easier to administer than interviews. In fact, some investigators have used structured interviews in the form of written questionnaires to elicit team knowledge (Blickensderfer, et al., 1997b; Blickensderfer, Cannon-Bowers, & Salas, 1997a; Jenkins & Rentsch, 1995). Relative to other elicitation methods, interviews and questionnaires have been used extensively to measure team knowledge. In particular, because of their independence from task performance, they have been used chiefly tomeasure team mental models which are thought to be less context-dependent and more stable over time than team situation models.

Process tracing techniques are methods for collecting data concurrently with task performance. These data are later analyzed to make inferences about the knowledge or underlying task performance. One of the most popular forms of process tracing relies on verbal reports provided while the participant is "thinking aloud" during task performance (vanSomeren, Barnard, & Sandberg, 1994). These reports can be retrospective, but it is typically believed that as long as there is no interference with the task itself, concurrent

reports provide more valid information regarding the current contents of working memory. Nonverbal data including keystrokes, actions, facial expressions, gestures, and general behavioral events have also been collected to trace cognitive processes and reveal underlying procedural knowledge. Like observations, process tracing data because of its on-line nature, lends itself well to the elicitation of quickly changing team knowledge.

Protocol analysis is the term used to describe various methods for summarizing and interpreting process tracing data (Ericsson & Simon, 1996). It typically involves transcribing the data, developing a coding scheme that captures the critical content of the data, applying the coding scheme to each identified unit in the protocol, and exploring frequencies, patterns, and sequential dependencies in the results. A relatively new area of inquiry that focuses on ESDA (Exploratory Sequential Data Analysis; Sanderson & Fisher, 1994) has produced some analytical tools and methods in recent years to facilitate this process. The combination of these new tools and event data captured on-line has promise as a way of overcoming many of the costs associated with knowledge elicitation, as well as providing alternative to interviews in rapidly changing environments.

Conceptual methods produce representations of domain concepts and their relations. Methods included in this set are cluster analysis (Johnson, 1967), multidimensional scaling (Shepard, 1962a; 1962b), Pathfinder (Schvaneveldt, 1990; Schvaneveldt, Durso, & Dearholt, 1989), and concept mapping (Jonassen, Beissner, & Yacci, 1993). In general, the methods take pairwise estimates of relatedness for a set of concepts and generate a spatial or graphical representation of those concepts and their relations. The general goal of these methods is to reduce the set of distance estimates in a meaningful way. Resulting representations can then be compared qualitatively and in many cases, quantitatively across groups and individuals. The techniques tend to be indirect in that they require judgments about conceptual relatedness, as opposed to introspections or explicit verbal reports. One advantage of these methods, particularly

for measuring team knowledge, is that they can handle results from multiple individuals, including summarizing data from several individuals and comparing data across individuals or groups. For this pragmatic reason, and because these methods target knowledge structure which is thought to be associated with team performance (e.g., Cannon-Bowers et al., 1993; Klimoski & Mohammed, 1994), applications of knowledge elicitation methods to team knowledge not using interviews and surveys, have relied on conceptual methods (Blickensderfer, et al., 1997b; Gualtieri, et al., 1996; Kraiger, et al. 1996; Mathieu, et al., in press; Stout, 1995; Minionis, et al., 1995; Walsh, et al., 1988).

These four categories represent the most commonly used methods for eliciting knowledge at the individual level. However, they are not all-inclusive. Task analysis methods, which analyze a task into it components (Kirwan & Ainsworth, 1992) and policy capturing approaches, which quantify decision policies (Dawes, 1979), target very specific aspects of individual knowledge and likewise, are additional possibilities for measuring team knowledge.

Mapping elicitation methods to team knowledge. There has been some analytical and empirical work directed at mapping methods for individual knowledge elicitation to type of knowledge that each elicits (Boose & Bradshaw, 1987; Geiwitz, Klatsky, & McCloskey, 1988; Geiwitz, Kornell, & McCloskey, 1990; Kitto & Boose, 1987, 1989; Meyer & Booker, 1990; Wielinga, Schreiber, & Breuker, 1992). From this information and the team knowledge measurement work done to date we can derive some preliminary conclusions regarding the mapping of team knowledge to elicitation method.

First, most of the approaches used thus far to elicit team knowledge have focused on the elicitation of team mental models. Specifically, interviews and paper-and-pencil questionnaires, along with conceptual methods such as multidimensional scaling and concept maps, are best suited for eliciting knowledge that is more stable and less situation-dependent than that associated with team situation models. Instead, these methods are best-suited for eliciting team mental models in that they are typically

administered off-line and are somewhat divorced from the immediate task context. This is not to say that team mental models are context-free, but rather they represent a more generic understanding of the task, the team, or the environment that transcends a specific situation. Also we can assume that the team mental model evolves over time with experience and knowledge acquisition of the team members, but on a time scale of weeks or months, so that in the time that it takes to administer interviews, questionnaires, and conceptual methods, the change has not been dramatic.

This is not the case for the ever-changing team situation model. The team situation model changes in concert with changes in the situation, which for many complex team tasks occurs at a rapid clip--too rapid for the off-line elicitation methods to capture. Further, because the team situation model is knowledge that represents the teams current understanding of the situation, it is extremely tied to the context of that situation. Off-line elicitation methods such as interviews and conceptual methods are generally weak at capturing the nuances and the information content of a specific situation. The on-line methods of observations and process tracing appear more promising for rapidly changing team knowledge and specifically, for team situation models.

Conceptual methods can also be adapted for the on-line elicitation required for situation model elicitation and in general, for elicitation in rapidly changing knowledge environments. For instance, the Pathfinder method described previously has been applied to the representation of sequential behavioral data using a methodology called PRONET (Cooke, Neville, & Rowe, 1996). Another way to adapt off-line knowledge elicitation methods to team situation model measurement is to stream-line them. In this case the goal is to make data collection (and even analysis and interpretation) stages more systematic and efficient. For instance, one way to streamline the pairwise rating method is to identify through prior testing, a subset of concept pairs for which rating responses were particularly diagnostic of team situation models. Ratings would then be collected on this subset as opposed to all pairs.

For the most part, however, elicitation methods have not been applied to team situation model measurement. Query methods such as SAGAT (Situation Awareness Global Assessment Technique; Endsley, 1990) and SPAM (Situation Present Assessment Method; Durso, Hackworth, Truitt, Crutchfield, Nikolic, & Manning, 1996) have been used to capture an individual's fleeting understanding of a situation and there have been some proposals for using these methods to assess team situation awareness as well (Cooke, et al., 1997). However, these are typically very specific queries such as "what is your current heading," and are better thought of as assessment methods, rather than elicitation methods, though elicitation (usually in the form of interviews) is needed to identify diagnostic queries.

In sum, a subset of knowledge elicitation methods has been applied to limited varieties of team knowledge. The measurement of situation models and knowledge in more dynamic domains has received relatively little attention. The application of a broader spectrum of knowledge elicitation methods to the problem of measuring team knowledge should open the door to the measurement of varieties of team knowledge previously untapped.

Team metrics

Although knowledge elicitation methods produce graphical structures or prototcols that provide qualitative data about team knowledge, for many reasons it is desirable to quantify this information. Particularly at the team level, quantification makes it easier to assess the accuracy of the knowledge, to aggregate individual results to generate a representation of team knowledge, or to compare individual results within a team to assess knowledge similarity. In fact, the relative ease with which certain elicitation methods are quantified provides yet another reason for the common application of conceptual methods (Blickensderfer, et al., 1997b; Gualtieri, et al., 1996; Kraiger, et al., 1996; Mathieu, et al., in press; Stout, 1995; Minionis, et al., 1995; Walsh, et al., 1988) or questionnaires (Blickensderfer, et al., 1997a; 1997b; Jenkins & Rentsch, 1995) to the

team arena. However, results of other knowledge elicitation methods such as unstructured interviews, observations, and verbal reports can also be quantified, though often with more effort. For instance, verbal responses or observed events can be categorized and the coded data can be quantified in terms of category frequencies. Even more information can be captured by examining transition frequencies between categories. Several systematic techniques for protocol analysis are instructive regarding these procedures (e.g., Cooke, et al., 1996; Ericsson & Simon, 1996; vanSomeren, et al., 1994).

In the following sections we review some metrics that can be derived from the results of knowledge elicitation methods and used to assess team knowledge. Some of these metrics have been commonly used and others are relatively novel. Illustrations of each metric are provided within the context of two elicitation examples. In both cases, we assume that the team is an aviation team with two team members (i.e., pilot and navigator).

The first example of elicitation is a traditional 10-item, four alternative, multiple choice test of declarative knowledge which lacks the open-endedness of a typical knowledge elicitation technique, and in fact, would be better described as an assessment method, but illustrates the metrics quite well. Hypothetical responses from each team member are presented in Table 2, along with the key to correct responses. The second example is a more typical conceptual elicitation method, which involves the collection of pairwise relatedness ratings of 5 task-relevant terms from each team member, and analysis of these data via the Pathfinder network scaling program (Schvaneveldt, 1990). Hypothetical rating responses and network results are presented in Figure 3. For both examples, we assume that the knowledge elicitation is perfect in that the domain knowledge can be completely captured by responses to the 10 items or 10 pairwise ratings.

[Insert Table 2 and Figure 3 about here]

Similarity metrics. Research on team knowledge has focused most often on the similarity of knowledge within a team, with "similarity" also referred to as consensus, convergence, agreement, compatibility or overlap among team members. In addition, there has been a general implication that high intrateam similarity should lead to the most effective teams (Blickensderfer, et al., 1997b; Converse, et al., 1991; Gualtieri, Burns, Phipps, Reeves, & Pierce, 1998; Rentsch & Hall, 1994; Stout, 1995). However, this assumption emphasizes the "hold in common" sense of knowledge sharing described previously, and undermines the "apportion" perspective which is most appropriate for heterogeneous teams in which team members have distinct roles and bring different views to the table. In heterogeneous teams at least some knowledge should be associated uniquely with distinct team roles, and for this knowledge intrateam knowledge similarity would be low. On the other hand, even for the most heterogeneous teams, some knowledge would likely be held in common and thus knowledge similarity would be a useful, albeit insufficient, descriptor of team knowledge.

How can similarity be measured? In the test example in Table 2 similarity can be measured in terms of the number or percentage of responses that are identical for two team members (6 or 60% in this case). In general, agreement is relatively easy to measure in cases in which there is a fixed set of potential responses and all team members respond to each query, as on a test or questionnaire. To leverage these advantages of tests, some researchers have taken an indirect approach and addressed team mental models in terms of shared expectations with the assumption that if the mental models are compatible then the expectations derived from them should be common (Blickensderfer, et al., 1997a; 1997b; Cannon-Bowers, et al., 1993). Expectations can be measured by questionnaires and overlap between questionnaire response can be measured via correlations or percent identical responses depending on the nature of the responses. Furthermore, intrateam similarity can also be thought of as a measure of interrater reliability at the group level (James, Demaree, & Wolf, 1984).

Output from conceptual methods can also be compared (Shaw & Gaines, 1988). For instance, the Pathfinder procedure is associated with a similarity measure (Goldsmith & Davenport, 1990) that is based on the proportion of shared links in two networks. In the example in Figure 3, the two resulting networks have 2 links in common (i.e., *route-weather* and *instr. check-take off*) out of a total of 9 unique links making the proportion of common links equal to .22. It turns out that there is a high probability (.30) of obtaining this similarity value by chance, and therefore, one would conclude that there is little evidence that the two networks are similar. A variety of investigators have used this metric to determine intrateam similarity (Blickensderfer, et al., 1997b; Cooke, Stout, Rivera, & Salas, 1998; Gualtieri, et al., 1996; 1998; Kraiger, et al., 1996; Stout, 1995). Other conceptual methods are associated with parallel means of determining similarity such as comparisons of concept centralities in UCINETs (Mathieu et. al., in press) and Euclidean distance between individuals or differences in dimension weights in multidimensional scaling solutions (Walsh, et al., 1988). Another alternative is to simply correlate the original pairwise ratings for each pair of team members (e.g., Blickensderfer, et al. 1997b). The Pearson correlation for the two sets of relatedness ratings in Figure 3 is -.22. Finally, to generate a team index of intrateam similarity the similarities for all pairs of team members would be aggregated in one of several ways described later.

The cases in which intrateam knowledge similarity has been measured have generally found reliable correlations between the similarity metric and measures of team performance or team process; high intrateam knowledge similarity being associated with the most effective teams (Heffner, Mathieu, & Cannon-Bowers, 1998; Mathieu, et al., in press; Minionis, et al., 1995; Stout, 1995; Walsh, et al., 1988). Interestingly, Mathieu et al., (in press) found this relationship to hold for teamwork, but not for taskwork and Minionis, et al. (1995) found that it held for tasks requiring interdependence and integrated team actions. This relationship between knowledge similarity and team

performance should only be expected for homogeneous teams or teams that are homogeneous with respect to the knowledge that is tested. However, even for a homogeneous team, knowledge similarity is an insufficient metric without some measure of knowledge accuracy.

Accuracy metrics. Whether one argues that teams should have similar or dissimilar knowledge, it is clear that accuracy is crucial. That is, all team members could have similar knowledge and they could all be dead wrong. Alternatively, in a heterogeneous team, all members could have dissimilar knowledge, yet overall, the team could be highly accurate. Indeed, Mathieu et al. (in press) found that accuracy and similarity interact to affect team performance.

How should accuracy be measured? In the test example it is simply the number or percentage correct for each individual, aggregated across the team. So in our example the pilot has 4 or 40% correct and the navigator has 6 or 60% correct. We could average their scores to get a team accuracy score of 50%. Note that in this example the two team members could have 100% similarity and 0% accuracy if they both responded in the same incorrect way to each response. Also, in this example, if team members respond differently to each item, the upper bound on the average team accuracy is 50% because half of the responses by definition will be incorrect. Accuracy could be higher however, in a case in which there were multiple "correct" responses.

To determine accuracy in the Pathfinder example, the network of each team member needs to be compared to a referent. The referent network could either be constructed logically by domain experts or empirically, by collecting ratings from domain experts. In addition, similarity between the team member's model and the referent model can be computed in several ways as described in the previous section. For purposes of the example in Figure 3, we assume that the referent network that represents a team member who had complete and accurate knowledge of both tasks would contain all nine of the unique links contained in the two networks in Figure 3.

Thus, the pilot has four of the nine referent links (44%) and the navigator has seven of them (78%). On average the team's knowledge is 61% accurate.

The few investigators who have looked at accuracy of team knowledge have done so in ways similar to the referent approach described above. Kraiger, et al. (1996) compared individual networks to those of a referent and averaged this value across team members to get team accuracy. They found that this team metric, which they labeled "complementary scoring strategy" was correlated with scores on a test of structural knowledge. Mathieu, et al. (in press) associated each team member's knowledge results with an expert of a particular ranking by using discriminant analysis. Team knowledge accuracy was found to be related to team process and team performance.

Although these accuracy metrics are relatively straightforward, they, like similarity metrics tend to assume that the team in question is homogeneous with respect to knowledge. The knowledge of each individual team member is compared to a referent which represents that knowledge pertinent to the team task. Thus, heterogeneous teams with individuals who specialize in a portion of the knowledge base would score poorly using this kind of global accuracy metric. However, it is precisely because an individual cannot master all of the task information that a team is required. Thus, what is needed is an accuracy metric for heterogeneous teams.

<u>Heterogeneous accuracy metrics.</u> According to the definition of teams offered earlier, team members are each given specific roles or functions to perform. Further, if we assume that this division of labor also corresponds to specific portions of the knowledge base, then mastery of this role-associated knowledge by each team member should be indicative of team knowledge for heterogeneous teams.

Although there has been little research in which heterogeneous accuracy has been measured, there are data that support the relation between heterogeneous accuracy and team performance. Gualtieri, et al. (1996), for instance, measured knowledge similarity among individuals with the same role, but on different teams, and found that within-role

similarity was greater than within-team similarity, supporting the need for heterogeneous knowledge measures. In addition, there is supporting evidence for the relation between role or interpositional knowledge and team performance when the former is manipulated through training interventions (Volpe, Cannon-Bowers, Salas, & Spector, 1996; Cannon-Bowers, Salas, Blickensderfer, & Bowers, 1998; Minionis, et al., 1995).

How should heterogeneous accuracy be measured? The basic requirement for such a measure is that the knowledge base be chunked or partitioned into units associated with each team member role. These chunks could consist of facts or concepts that are either unique to each role or that are partially unique in that some concepts overlap roles. For instance, in the multiple choice test example, we can divide the knowledge base into unique chunks by assuming that the odd numbered questions pertain to the pilot position and the even numbered questions, to the navigator position. From this information we can derive the percentage of role-relevant items responded to correctly by each team member. The pilot has 2/5 or 40% of the pilot items correct and the navigator has 3/5 or 60% of the navigator items correct. This gives us an average of 50% heterogeneous accuracy for this team.

Chunks may also consist of the same material or concepts, but may represent a different view or perspective on that information. For example, using the Pathfinder example, different perspectives on the same concepts can be represented as role-specific referent networks in which the concepts are identical, but the links between concepts vary. In particular, assume that the successful pilot should have links between *take off* and *instrument check* , *take off* and *weather,* and *route* and *weather,* whereas the successful navigator should have links between *weather* and *take off, weather* and *reach altitude* and *route* and *instrument check.* Thus, out of the five unique links associated with the pilot and the pilot-referent, two are shared (40%). The navigator shares 3 out of 7 links with the navigator referent (43%) resulting in 42% team heterogeneous accuracy.

The flip side of heterogeneous accuracy is accuracy with respect to the knowledge associated with roles other than your own, or interpositional accuracy. Even members of heterogeneous teams may be versed in some of the knowledge pertinent to other positions. This is, in fact, the goal of cross training--to increase the team members' understanding of the task from the others' points of view (Cannon-Bowers, et al., 1998). The degree to which an individual has mastered role-oriented information over interpositional information provides an indication of degree of specialization. A team with high heterogeneous accuracy or with high interpositional accuracy may or may not be specialized. Specialization depends on the relative mastery of the position-specific material over the interpositional material.

In the multiple choice example, the pilot has 2/5 or 40% of the navigator items (even-numbered) correct and the navigator has 3/5 or 60% of the pilot items (odd-numbered) correct. Because the differences between these scores and the heterogeneous accuracy scores is 0 for each individual and thus, 0 for the team, we could conclude that this particular team is not highly specialized. A zero (or negative) difference indicates that team members know as much or more about other positions as they do of their own. Likewise, the similarity between each team member's network and the other team member's referent can also be calculated (0 for the pilot and 43% for the navigator). Thus, in this example heterogeneous accuracy is at 42%, and interpositional knowledge at 22%. The difference is 20%, indicative of more specialization than in the multiple choice example.

These metrics associated with heterogeneous accuracy have received preliminary support. Cooke, et al.(1998) found that over the course of a team study, teams who were largely heterogeneous and specialized after training, tended to increase in terms of interpositional accuracy and decrease in specialization. The degree to which this shift occurred was related to effective team performance.

There are other possibilities for heterogeneous accuracy metrics as well. For instance, Jenkins and Rentsch (1995) conceive of and measure "schema accuracy" in terms of the team member's ability to describe another member's schema--accurate knowledge about another's knowledge, much like the measure of interpositional knowledge described above. The metric is based on the sum of the absolute difference between ratings of importance made by a team member about another team member and the same ratings made by that team member in question. Jenkins and Rentsch (1995) label the combination of this metric and an agreement metric, "coorientation." They found that the interpositional metric predicted team effectiveness to a greater extent than intrateam similarity, supporting the general importance of heterogeneous metrics.

Heterogeneous accuracy metrics provide a means of evaluating the degree to which individual team members have mastered portions of the knowledge base, and hence focus on how each team member's knowledge maps onto portions of the knowledge base, rather than how portions of the knowledge base map onto individual team members. So, these measures do not indicate the extent to which a particular concept or fact has been mastered by the team. Unless heterogeneous accuracy is perfect (i.e., 100%), there is no guarantee that each concept has been mastered by at least one team member. That is, the heterogeneous accuracy metrics do not reveal gaps in the knowledge base. In addition, although teams with high interpositional accuracy will tend to have knowledge that is more distributed across team members than a team with low interpositional accuracy, the degree to which each concept or fact is distributed is not revealed. These issues can be resolved, however, with knowledge distribution metrics.

Knowledge distribution metrics. Team knowledge, like individual knowledge may be associated with gaps or missing information. One benefit of a team is that many gaps in individual knowledge can be compensated for by the knowledge of other team members. However, gaps in team knowledge may be particularly critical such as when all team members of a flight crew know how to take-off, but no one knows how to land.

In general, the manner in which specific knowledge is distributed among members of a team may be a critical factor in team performance (Hutchins, 1995).

Along these lines, Walsh, et al. (1988) distinguish agreement among belief structures from information coverage. Walsh et al. (1988) measure coverage in terms of individual weights on dimensions in multidimensional scaling solutions. If all dimensions are highly weighted by at least one team member then coverage is good. They found that coverage predicted team performance, but that surprisingly, low coverage was associated with better performance than high coverage. Note that the concept of coverage necessitates some standard against which to judge completeness (in this case the set of MDS dimensions).

How should knowledge distribution be measured? In the test example, in which it is assumed that the domain is completely covered by the set of 10 items, items 2, 3, and 7-10 were answered correctly by at least one team member, so we could say that the team has mastered 60% of the knowledge base. Further, four of these six mastered items were answered correctly by both team members, so we could say that 40% of the knowledge is redundantly distributed across team members, 20% is uniquely distributed, and 40% is not covered. This same kind of analysis could be done considering role-associated portions of the knowledge base, rather than individual items. In the test example, a criterion of 60% might be established to indicate mastery of either the pilot or navigator role. If this were the case, there would be mastery of both roles with the navigator alone mastering each so that knowledge distribution would be considered unique.

The Pathfinder-based metric for knowledge distribution is similar. At the role level for instance, mastery can be defined as having at least 60% network similarity with the role referent. In the example in Figure 3, no individual has mastered either role, so that there is 0 coverage for this information. In addition, mastery of a single concept can be defined in network terms as the proportion of shared links associated with that concept

for a given network and a referent. As in the illustration of accuracy, the referent network is assumed to be the nine links in the union of links in the two networks of Figure 3. Thus, the mastery of the concept *route* is based on the presence of the three links connecting route to each of *reach altitude, instrument check, and weather.* The pilot has one of these links and the navigator has all of them resulting in 33% and 100% respective concept mastery scores. Concept mastery can be computed for each of the other concepts in the same way. In this example, the pilot has 25% mastery of *reach altitude* , 66% mastery of *take off,* and 50% mastery of the remaining items, whereas the navigator has 66% mastery of *take off* and 75% mastery of the remaining items. A cutoff value for proportion shared links can be used to classify concepts as mastered or unmastered and to ultimately identify the degree to which conceptual knowledge distributed among team members. In this example, if at least 60% mastery is required, then the team, in this case the navigator, has complete coverage of the five items, however the knowledge is uniquely distributed among team members.

Mapping team metrics to team knowledge. The team metrics described above can be applied to results from any of the elicitation methods. There are some preconditions however, including the ability to assess similarity between the two elicitation outcomes, and in the case of accuracy and distribution metrics, some assumptions about the knowledge required of the team or of individual roles. Although the team metrics are not specific to type of knowledge or rate of change of that knowledge, the choice of a metric does depend on assumptions regarding the distribution of that knowledge among team members. Under assumptions of homogeneous distribution in which all team members possess more or less the same knowledge, similarity and accuracy metrics are appropriate. Under assumptions of heterogeneous distribution, however, the heterogenerous accuracy and knowledge distribution metrics are relevant. In the following section we describe methods for aggregating the metric values obtained for

individual team members (accuracy, heterogenerous accuracy) or pairs of team members (similarity) in order to generate a single value representative of the team as a whole.

Aggregation Methods

Given a metric derived from a collective measurement approach (i.e., administered to individual team members), how should this metric be combined across team members to produce a metric representative of the team as a whole? There are many ways to aggregate, although most researchers have averaged the individual data (Blickensderfer, et al., 1997a; 1997b; Jenkins & Rentsch, 1995; Kraiger, et al., 1996). However, the danger in averaging is that, due to team member variance, the averaged result may be unrepresentative of any single team member. Alternatively, some investigators have approached aggregation by using the median value (Hinsz, 1995) or by relying on responses given by the majority (Minionis, et al., 1995) or all (Gualtieri et al., 1996) of the team members. The two generic aggregation methods represented in Figure 1 represent any two of the many possibilities.

There are other possibilities too, such as taking the sum, the minimum or maximum, value, or the range. The minimum and maximum strategies would represent team knowledge to the extent that knowledge was a function of the strongest or weakest team member. For instance, one member's knowledge may predict team performance on an aspect of the task that relies heavily on that individual (e.g., piloting a plane). Blickensderfer et al., (1997b) found that the best predictor of team performance was when the aggregate for a shared representation survey was based on the minimum intrateam pairwise correlation for responses on that survey. The range may be a good measure of team knowledge to the extent that intragroup variation on some measure is predictive of team knowledge (e.g., teams that are heterogeneous on some knowledge measure may be more or less effective than teams that are more or less consistent). Finally, Walsh, et al. (1988) distinguished potential team knowledge from actual team knowledge, the latter being based on an aggregate that was weighted by the degree to

which team members participated in team activities. The idea here was that the knowledge of the more vocal, active team members would play a greater role in determining the knowledge of the team as a whole.

Clearly there is no definitive method for aggregating individual data and no clear means of using the team knowledge features to select an aggregation method. Research is needed to comparatively evaluate these and other methods. As a general rule, however, it is good policy to avoid averaging team member data that vary greatly and to instead rely on an alternative approach like taking the minimum or maximum.

One final note regarding aggregation is that it may be more meaningful to use the individual metrics to discretely categorize a team, rather than to characterize it by an aggregate score. For example, Cooke, et al., (1998) collected pairwise relatedness ratings for task-related concepts from each team member. A measure of intrateam similarity was derived by summing rating correlations or network similarity measures for each pair of the three team members. Although the resulting metric was not generally predictive of performance, a different picture emerged when a median cutoff was used to determine pairwise team member similarity. This information was used to generate the patterns displayed in Figure 4. Interestingly, Pattern A is associated with the most effective team and Pattern B with the least effective. Further exploration of this kind of discrete representation of team metrics seems warranted.

[Insert Figure 4 about here]

Conclusions

Team knowledge is central to a number of theoretical explanations of team performance ranging from team decision making to team situation awareness. There has been much speculation concerning the nature of team knowledge and the role that it plays in team cognition and performance. In addition, recent applications in team training and team assessment require an approach that goes beyond assessment to uncover the content and structure of team knowledge. Only recently have investigators begun to explore

measures that might capture the essence of team knowledge. The majority of the research on this topic has focused on the measurement of the more stable and generic team mental models, has used methods of interviews, questionnaires and conceptual methods to elicit this knowledge, and has derived metrics of similarity and to a lesser extent, accuracy from the results of these methods. To this point the results are promising, with these measures of team mental models corresponding to various team process and performance measures.

[Insert Table 3 about here]

Despite this progress, much remains to be done. Table 3 lists some future research directions in terms of methodological requirements for the measurement of team knowledge. First, current methods for eliciting team knowledge all approach elicitation from the level of the individual. Because team knowledge is thought to be more than the sum of individual team members' knowledge, holistic approaches to measurement are needed which elicit knowledge from the team as a whole. Second, team knowledge elicitation and knowledge elicitation methodologies in general, need to address the more fleeting, context-specific understanding of a situation that we call team situation models. This type of knowledge is thought to underlie team situation awareness (Cooke, et al., 1997; Stout, et al., 1996) and other team behavior in complex dynamic tasks. In fact, in tasks in which the situation is continually and rapidly changing, team differences in this dynamic understanding may account for the most variance in team behavior. As a first step, we have suggested some ways that current elicitation techniques could be adapted or modified for this job that, for example, rely on data collected unintrusively during the course of team performance (i.e., keystrokes, communication events). Other approaches should be considered as well.

Additional work is also needed on metrics that take the output of the knowledge elicitation methods and produce values that are meaningful in respect to team knowledge. There are a number of interesting metrics that can be derived from elicitation data that

can represent team knowledge in heterogeneous teams. The heterogeneous accuracy and knowledge distribution metrics only scratch the surface. In general, more measurement work is needed that reflects the heterogeneity assumed to be central to the accepted definition of teams.

Further exploration of ways to discretely classify teams based on these metrics also appears to be a promising direction. Two teams may have the same average intrateam similarity value, but are differentially classified when the pattern by which similarity is dispersed is taken into account. The pattern may better reflect team knowledge.

Furthermore, the methods and metrics discussed in this paper follow from a specific theoretical view of team knowledge, but there are other views. More importantly, there are other factors that are not addressed by this view, but that seem to be relevant to team knowledge such as attitudes of team members or positions of authority on the team. In addition, there are related approaches that may also be relevant to team knowledge such as dynamic systems and multiple distributed agents. Additional promising methods and metrics may arise from a broader view of team knowledge.

Finally, despite the most prolific methodological developments in this area, the methods are only valuable to the extent that they have been validated and that they are associated with principles for selecting appropriate methods in a given situation. The variety of metrics described in this paper illustrate the richness and complexity of team knowledge measurement. The innumerable combinations of knowledge elicitation method, team metric, and aggregation method, not to mention the future possibilities of holistic and continuous elicitation methods, can seem overwhelming. However, given that team knowledge is equally multifaceted, such options seem necessary. Many methodological decisions can be guided analytically by the nature of the team knowledge that is to be measured and by the specific features of the measurement methodology (e.g., use conceptual methods or interviews or questionnaires for measuring team mental models; use heterogeneous accuracy metrics for determining the accuracy of a team task

associated with distributed roles and knowledge). As measurement methods are continually refined are used in team research, additional guidelines for their usage should be revealed.

Additionally, empirical validation can also speak to the selection of an appropriate methodology. Measures of team knowledge should be reliable. They should also be valid in that they differentiate teams that are assumed to differ in the targeted team knowledge, either as a result of experience or manipulation of the training or task environment. Further, given that team knowledge is relevant to team performance, then effective measures of team knowledge should correspond to differences in team performance. It is also useful to compare multiple measures of team knowledge or variations in the same measure against these criteria. Limited empirical evaluations of team knowledge measures have been conducted. For instance, knowledge elicitation methods have been comparatively evaluated in experiments at the level of individual elicitation, but more work is needed on applications of these methods to the team front. Also as previously described, empirical evaluative data exists for similarity and accuracy metrics, but not for heterogenerous metrics.

It is likely that the most mileage (in a sense of predicting team performance) is to be gained by using composite measures. For instance, it may be that some combination of knowledge similarity, knowledge distribution, and heterogeneous accuracy is associated with optimal team performance in a given domain. Cooke, et al. (1998) found that for a relatedness rating-based measure, both overall knowledge accuracy and interpositional knowledge accuracy predicted team performance in a simulated helicopter mission, with better teams being more accurate and having more accurate interpositional knowledge. Additionally, Minionis, et al. (1995) successfully employed a single measure of overlap that took both agreement and accuracy into account. Comparative evaluations should also suggest promising suites of methods.

In conclusion, the measurement of team knowledge, though challenging, stretches the limits of existing measurement approaches and cognitive theories. Traditional theories and measures have been developed, applied, and evaluated for much simpler tasks in single-operator settings. Investigations of team knowledge and the development of appropriate measures of team knowledge extends previous work to complex sociotechnical environments. This rich context is, after all, where much cognition occurs and where many applied problems begin.

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Table 1. A framework for circumscribing *team knowledge*. This paper focuses on that part of team cognition that is within the box.

Team Cognition

Team Decision Making

Team Situation Awareness...

Team Knowledge

Team Mental Model

- long lasting, exists prior to task
- acquired through training, experience etc.
- a variety of content (taskwork, teamwork)
- a variety of forms (declarative, procedural, strategic)
- function: collective knowledge base, leads to common expectations

Team Situation Model

- fleeting, dynamic
- acquired during task using team mental model and world cues
- situation-specific
- function: interpret situation in compatible way

...Team Perception

Table 2. Example of elicitation of factual knowledge for two team members (pilot and navigator) using a 10-item multiple choice test.

Item No.	Correct Responses	Pilot's Responses	Navigator's Responses
1	a	c	d
2	c	a	c
3	d	b	d
4	a	b	c
5	a	d	d
6	b	c	c
7	d	d	d
8	b	b	b
9	c	c	c
10	c	c	c

Table 3. Methodological needs for the measurement of team knowledge.

---

1) Development of holistic team knowledge elicitation methods.
2) Adaptation and development of methods for eliciting team situation models including...
    a. the adaptation of process tracing and observation methods
    b. the use of team behavioral data as input to conceptual methods (e.g.,PRONET; Cooke, et al., 1996)
    c. stream-lining of off-line elicitation methods.
3) Further development of metrics that reflect team heterogeneity.
4) Exploration of discrete classifications of teams based on metrics.
5) Develop measures that reflect an even broader view of team knowledge.
6) Further develop the principles for mapping a specific measurement method onto team knowledge characteristics.
7) Test the predictive validity of various elicitation methods, metrics, and aggregation methods in terms of their ability to predict team process behaviors and team performance.
8) Comparative evaluations of various elicitation methods, metrics, and aggregation methods against each other.

Figure Captions

Figure 1. Characteristics of targeted team knowledge and team knowledge measures.

Figure 2. Collective and holistic approaches to the measurement of team knowledge

Figure 3. Example relatedness ratings from two team members (pilot and navigator) and the associated Pathfinder networks.

Figure 4. Four patterns of knowledge similarity among team member pairs. P=pilot, NO=navigation officer, IO=intelligence officer. Those enclosed in the same circle have similar conceptual structures based on a median cutoff. Highest performing team is team 9, lowest performing team is team 8. Team 2 was ranked second after team 9 on two of the four performance measures

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TARGETED TEAM KNOWLEDGE

TYPE	**RATE OF CHANGE**		
	slow	**average**	**fast**
team mental model			
homogeneous			
heterogeneous			
team situation model			
homogeneous			
heterogeneous			

MEASUREMENT APPROACH

AGGREGATE-1	**TEAM METRIC**			
ELICITATION METHOD	similarity	accuracy	heterogeneous accuracy	knowledge distribution
observation				
interviews & surveys				
process tracing				
conceptual methods				
AGGREGATE-2				
ELICITATION METHOD				
observation				
interviews & surveys				
process tracing				
conceptual methods				

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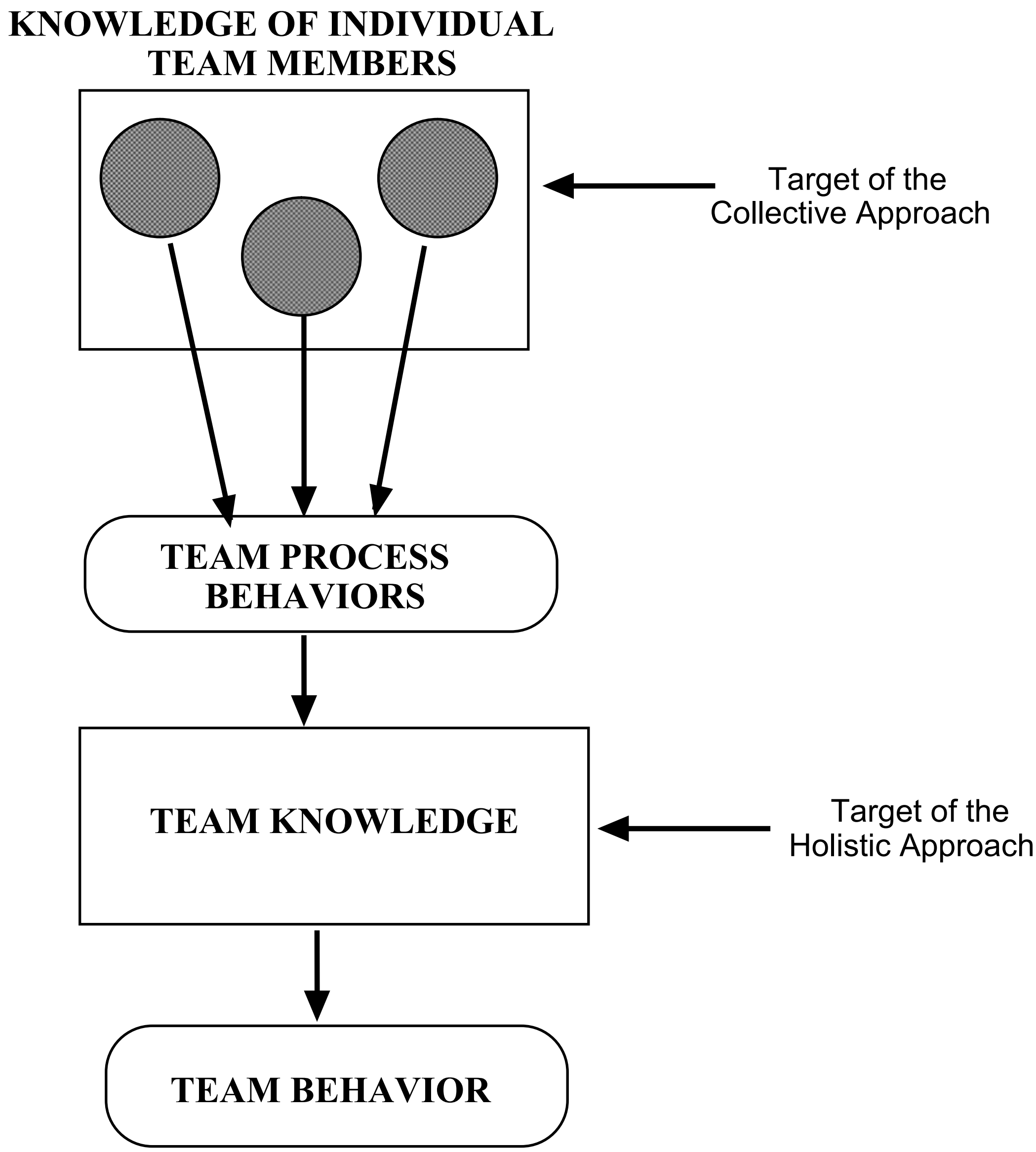

KNOWLEDGE OF INDIVIDUAL TEAM MEMBERS
Target of the Collective Approach
TEAM PROCESS BEHAVIORS
TEAM KNOWLEDGE
Target of the Holistic Approach
TEAM BEHAVIOR

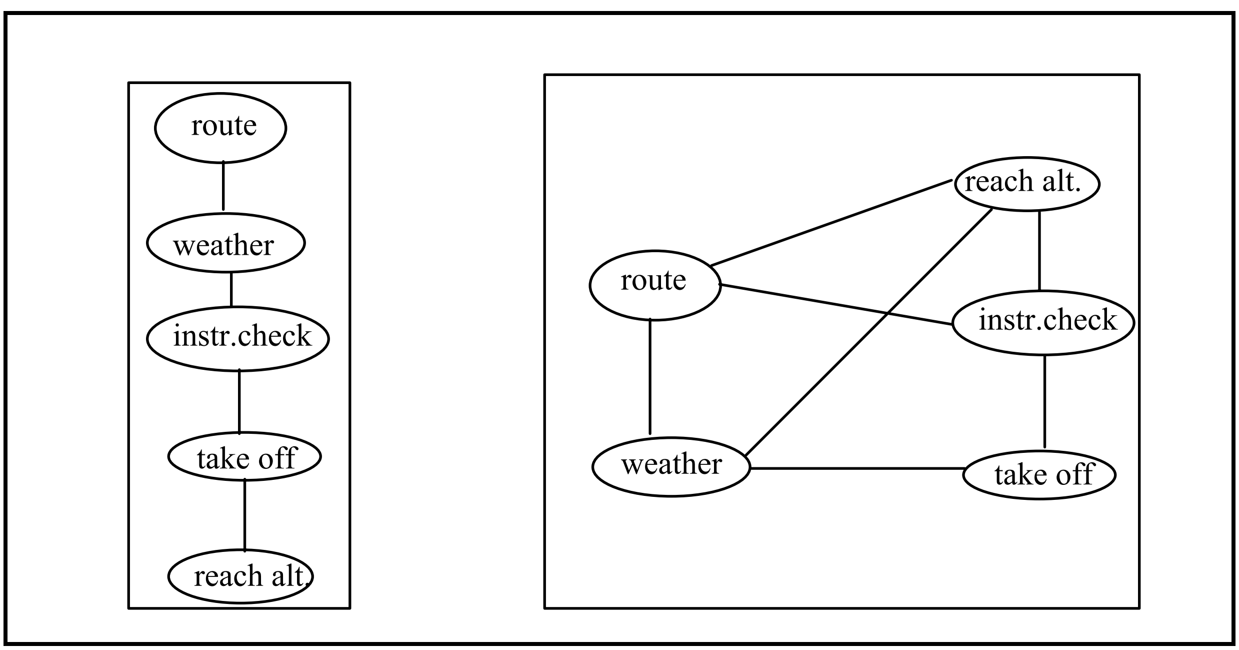
Pilot's relatedness ratings j(1=related, 5=unrelated):

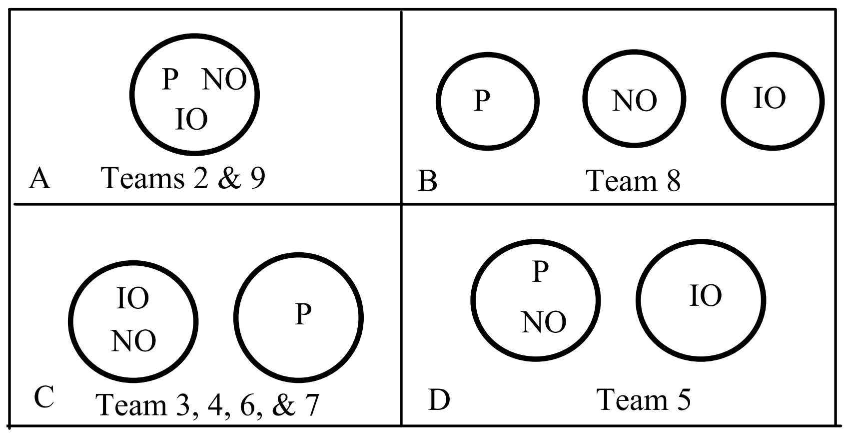
	route	weather	inst. check	take off	reach alt.
route	0	-	-	-	-
weather	1	0	-	-	-
instrument check	2	1	0	-	-
take off	3	2	1	0	-
reach altitude	4	3	2	1	0

Navigator's relatedness ratings (1=related, 5=unrelated):

	route	weather	inst. check	take off	reach alt.
route	0	-	-	-	-
weather	1	0	-	-	-
instrument check	1	3	0	-	-
take off	3	1	1	0	-
reach altitude	1	1	1	3	0

Pilot's Pathfinder Network **Navigator's Pathfinder Network:**




P NO
IO
A Teams 2 & 9
P
NO
IO
B Team 8
IO
NO
P
C Team 3, 4, 6, & 7
P
NO
IO
D Team 5